Transport Policy 115 (2022) 4–13

Contents lists available at ScienceDirect

Transport Policy

journal homepage: www.elsevier.com/locate/tranpol

Containing the spatial spread of COVID-19 through the trucking network[☆]

Agustina Calatayud, Felipe Bedoya-Maya [*], Santiago Sánchez González, Francisca Giraldez

Transport Division, Inter-American Development Bank, Washington D.C, 20577, United States

A R T I C L E I N F O

Keywords:
Transport networks
Trucking
COVID-19
Risk management policies
Latin America

A B S T R A C T

The trucking industry is the backbone of domestic supply chains. In the context of the COVID-19 pandemic, road transportation has been essential to guarantee the supply of basic goods to confined urban areas. However, the connectivity of the trucking network can also act as an efficient virus spreader. This paper applies network science to uncover the characteristics of the trucking network in one major Latin American country −Colombia− and provides evidence on freight networks' ability to spread contagious diseases spatially. Network metrics, official COVID-19 records at the municipality level, and a zero-inflated negative binomial model are used to test the association between network topology and confirmed COVID-19 cases. Results suggest that: (i) the number of COVID-19 cases in a municipality is linked to its level and type of network centrality; and (ii) being a port-city and a primary economic hub in the trucking network is associated with a higher probability of contracting earlier a pandemic. Based on these results, a risk-based approach is proposed to help policymakers implement containment measures.

1. Introduction

Accounting for more than 70% of the volume and 80% of the value of domestic freight movements, trucking is the primary transportation mode within countries in Latin America (Barbero and Guerrero, 2017; Londoño-Kent, 2007). In 2019, road transportation mobilized 81% of freight in Colombia (97% when excluding oil and coal), for a total of 247 million tons distributed in 35 million trips (7.05 tons per trip) across the country (MinTransporte, 2019). There are approximately 3400 trucking companies in Colombia, with half of them operating in the long-haul segment. In addition, informal transportation accounts for an estimated 40% of freight movement (El Tiempo, 2001; MinTransporte, 2019).

Ensuring trucking operations' continuity during the COVID-19 pandemic has been critical to guarantee the supply of essential goods to confined urban areas. Trucking is the only transport mode connecting production nodes with seaports and local consumption centers for most regions. However, in the context of an epidemic outbreak, the connectivity of a transport network can also act as an efficient virus spreader (Meloni et al., 2009). For example, among the first COVID-19 cases reported in Colombia was a 55-year-old long-haul truck driver who drove across the country from the border of Venezuela to the port of Buenaventura on the Pacific coast; he only developed symptoms once he arrived in Buenaventura. Likewise, one of the first positive cases of COVID-19 in Uruguay was a truck driver from Argentina that drove to Montevideo. Unfortunately, his case was confirmed when he was already back in Buenos Aires.

In many developing countries, COVID-19 safety protocols for the trucking industry were not implemented until several weeks after the first cases were reported. For example, in Colombia, these measures were issued on April 24, 2020, by the Ministry of Health and Social Protection (Minsalud, 2020). The absence of regulation created numerous operational hurdles and uncertainties for trucking companies, with longer waiting times and the need to stop at various intermediate checkpoints when driving through different jurisdictions. Overall, it increased the risk of COVID-19 expansion through the trucking network. This paper shows to what extent it did so by uncovering the characteristics of the Colombian trucking network and identifying the level of exposure to virus spatial propagation for each municipality. Network and statistical methods were combined to detect critical road connections for virus propagation. Based on this analysis, we propose a risk-based approach to help policymakers implement containment

[☆] The opinions expressed in this article are those of the authors and do not necessarily reflect the views of the Inter-American Development Bank, its Board of Directors, or the countries they represent.

[*] Corresponding author.
E-mail addresses: mcalatayud@iadb.org (A. Calatayud), fbedoyamaya@iadb.org (F. Bedoya-Maya), santiagosa@iadb.org (S. Sánchez González), franciscag@iadb.org (F. Giraldez).

https://doi.org/10.1016/j.tranpol.2021.10.022
Received 5 October 2021; Accepted 27 October 2021
Available online 1 November 2021

measures while ensuring business continuity in the trucking industry, thus improving critical supply chains' resiliency.

The paper is organized as follows: Section 2 reviews the extant literature on virus propagation and transport network dynamics; Section 3 briefly describes the trucking sector in Colombia in the context of the COVID-19 emergency; Section 4 presents the methodology to explore the association between the trucking network topology and the spread of COVID-19 in Colombia; Section 5 presents the results; Section 6 discusses the findings; and Section 7 concludes.

2. Literature review

A viral infection spreads as the virus passes from host to host (Balcan and Vespignani, 2011). In the case of coronaviruses, the spatial spread is a function of a person's degree of connectivity and his/her ability to transport the virus to new places (Iacus et al., 2020). An extensive literature in epidemiological research studies the association between the transmission risk of infectious diseases and transport networks. These studies are based on two assumptions: first, propagation occurs through contacts among individuals linked by social networks (Kretzschmar and Morris, 1996); second, populations are spatially isolated but connected through transportation. This approach allows a simple though clear understanding of mobility patterns and their relationship with virus transmission, either at the individual or group level (e.g., city, municipality) (Li et al., 2021). Indeed, Bian & Liebner (2007) show that individuals' spatial distribution and mobility facilitate understanding the spatial heterogeneity in infectious disease transmission. Related to this, Mao and Bian (2010) use dynamic social network analysis to assess the efficacy of travel-based, contact-based and random vaccination programs, finding that inter-community travel should be of primary relevance when choosing proper vaccination strategies.

Air travel has been one of the primary spatial spreaders of infectious diseases for the past two decades (Yang et al., 2015). Khan et al. (2009) investigated how travelers departing from Mexico City disseminated the H1N1 virus worldwide and simulated future virus transmission based on the air transport network's topology. Yang et al. (2015) showed that the network's structural properties significantly affected epidemic spreading and outbreak in traffic-driven spreading dynamics, with network hubs disseminating infections faster and at a larger scale. Poletto et al. (2012) suggested that, together with network topology and hosts' movements, the length of stay at destination significantly impacted the threshold conditions for the global epidemic invasion.

Extant literature has also analyzed mobility patterns at the city level to understand local transmission. Balcan and Vespignani (2011) found a transition phase during virus dissemination between when only a subgroup is affected and when contagion affects the network on a large scale, where commuting patterns determine the threshold. Xu et al. (2013) studied the spread of an infectious disease through public transport systems, suggesting that these are a bridge through which infections travel from one location to another and a place of contagion given the proximity between travelers. Their findings recommend increasing transportation efficiency and improving sanitation and ventilation to decrease an outbreak's chance of spreading further. Yang and Wang (2016) analyzed the control of traffic-driven epidemic spreading by immunization strategy, considering random, degree-based, and betweenness-based strategies. Their results suggest that outbreaks can be effectively suppressed when a small fraction of nodes with the highest betweenness centrality are vaccinated.

Research on the outbreak of COVID-19 in China found a positive correlation between confirmed cases at the national level and the total number of passengers traveling outside the Hubei province (Kraemer et al., 2020; Zhao et al., 2020). Iacus et al. (2020) used the variation in the European Union mobility restrictions implemented independently by the member states to analyze virus dissemination, showing that mobility alone could explain up to 92% of France and Italy's initial spread. In the United States, Harris (2020) explored the relationship between subway ridership and the virus' spatial distribution in New York, suggesting that the subway system was a significant disseminator of COVID-19 infection during the initial pandemic wave. Badr et al. (2020) quantified the relationship between social distancing and COVID-19 propagation using mobility patterns between counties in the United States as a proxy for social distancing. Their results show a substantial benefit from mobility reductions in decreasing virus transmission, with benefits being perceptible between nine days and up to three weeks after implementing restrictions. Carlitz and Makhura (2021) analyzed the impact of shelter-in-place orders in South Africa, finding that mobility reductions were significantly associated with lower COVID-19 growth rates two weeks after implementation. Likewise, Lawal & Nwegbu (2020) showed that the growth of COVID-19 cases in Nigeria during the national lockdown could be mainly attributed to the different levels of compliance across provinces. Zhang et al. (2020) analyzed the epidemic correlations across 22 countries in six continents before and after implementing international travel restriction policies, suggesting that restricting air travel in hotspot areas with high infection rates is less effective than adopting more integrated and internationally coordinated movement restrictions.

While available literature has mainly focused on air travel and public transport systems to uncover the relationship between infectious diseases and mobility, there is still little understanding of the risk that freight transportation may pose for virus outbreaks. Previous studies on blood-borne and sexually transmitted diseases have found a positive association with trucking activity (Apostolopoulos and Sönmez, 2007). Through millions of daily trips, trucking networks connect thousands of cities in a country. Truck drivers travel long distances and interact with individuals from different communities, becoming a risk for acquiring and spreading an epidemic (Apostolopoulos et al., 2015). In addition, the trucking work nature implies many interactions at rest stops, terminals, check-in points, and other intermediate points (Apostolopoulos et al., 2014). In these locations, social ties are formed with heterogeneous agents of the society, such as other drivers, cargo dispatchers, registry and customs clerks, drivers of private vehicles that stop at petrol and personal consumption points, friends, and family (Apostolopoulos et al., 2016). In the presence of a highly contagious virus, truck drivers' work represents a real challenge for policymakers, as these jobs are crucial to maintaining the supply of essential goods, being hardly possible to eliminate social interaction from it (Ranney et al., 2020).

Bajunirwe et al. (2020) is among the few studies investigating trucking activity and the transmission of COVID-19. The authors analyzed the first ten weeks from the first COVID-19 case reported in Uganda and found a strong relationship between the level of contagion and trucking activity. As of May 29, 2020, 71.8% of confirmed cases corresponded to truck drivers. Gachohi et al. (2020) reported an increase in HIV and a greater risk of contagion of COVID-19 in East Africa due to longer waiting times by truckers at their various intermediate stops. In Qingdao, China, Liu et al. (2020) found COVID-19 particles in imported frozen products close to being dispatched by the different transport modes to local markets. However, to the authors' knowledge, there is still no study that assesses the extent to which the topology of trucking networks contributed to the spread of COVID-19. As evidenced by extant literature in epidemiology, network theory can be a valuable tool to explore this question. For example, as highlighted in Kitsak et al. (2010), a trucker with relatively fewer connections may have a greater capacity to spread the virus than a trucker with more connections, depending on their position in the freight network, the community, and the type of relationships between nearby nodes.

This paper aims to fill in this research gap by combining network science and statistical methods. With a focus on Latin America, this paper studies a region often overlooked by the available literature that analyses virus transmission and mobility. This region became an epicenter of the COVID-19 pandemic in July 2020 and, since then, has faced several waves of increased cases. In Colombia, the number of accumulated confirmed cases as of August 14, 2021, was 4.9 million, with 41.2 thousand active cases and 123.4 thousand deaths (Minsalud, 2021). By better understanding all the factors that contribute to virus transmission, policymakers will be able to design more effective measures that, at the same time, enhance truck drivers' safety, reduce the risk of the spatial virus spreading, and avoid supply chain disruptions.

3. Colombia in the COVID-19 context

This paper focuses the analysis on Colombia, the fourth-largest economy in Latin America, where nearly 97% of domestic cargo−excluding oil and coal−is mobilized by road transportation (MinTransporte, 2019). Due to the lack of a consolidated rail system, trucking has historically been the only option to transport goods from production centers to seaports and urban areas. In addition, the road network's connectivity allows trucking to reach remote areas, such as the Amazon and the Orinoco Regions, rainforest areas located southeast of Bogota, the country's capital city (Fig. 1).

The first positive case of COVID-19 in Colombia was reported north of Bogota on March 6, 2020. It was a 19-year-old patient that arrived from Milan, Italy. Three days later, a case was reported in Medellín, the second-largest city in the country. On March 24, with 378 confirmed cases, the government issued a shelter-in-place order at the national level, closing all non-essential activities (INS, 2021). While the Presidential Decrees 457 and 636 restricted mobility at national and state levels, it allowed companies authorized by the Colombian Trucking and Logistics Association (Colfecar, for its acronym in Spanish) to continue operating and guarantee the supply of essential goods to urban populations. In addition, the decrees suspended toll payment for truckers as an incentive to continue activities across the country. Although the sector was severely affected by the drop in domestic and international trade and the restrictions applied by local authorities on passenger movements, 70% of authorized companies continued operating, moving mainly corn, rice, and palm oil from production areas to seaports on both Caribbean and Pacific coasts (MinTransporte, 2020). On April 24, 2020, the Ministry of Health and Social Protection issued the COVID-19 safety protocols to be implemented by the trucking industry.

Fig. 1. Colombian road network.
Source: Logistics Cluster (2014).

4. Methodology

The drastic drop in passenger movements due to the national quarantine implemented by the government, the continuity of freight transportation, the delay in implementing safety protocols, and the gradual spread of the virus throughout the national territory present a unique opportunity to evaluate the association between road transportation and the spread of the COVID-19 disease in Colombia. To this end, we first built the trucking network by using truck origin-destination (O-D) data from the Logistics National Observatory (ONL, for its acronym in Spanish). The ONL provides annual information on a representative sample of 659,334 trips for 2010–2016 for a total of 3780 O-D pairs. To control for any factor that might have altered trucking in a given year, such as inclement weather, road closures, or strikes, we avoided selecting one particular year and instead calculated the annual average number of trucks for each O-D pair, based on data from a seven-year timeframe (2010–2016). To capture regular trips, we exclude O-D routes with less than 100 trucking trips. The routes excluded account for 10% of the total O-D routes. Chiefly, they show a median number of trips per month of less than one, therefore not involving regular human interactions in trucking-related activities, as discussed by Iacus et al. (2020). Finally, locations were grouped according to the geographical units used by national statistics to report COVID-19 cases.

Data was collected on the total number of COVID-19 cases from the National Institute of Health (INS, for its acronym in Spanish), for the period March 6, 2020−when the first case was confirmed−to May 6, when the pandemic was present in 30% of the geographical units and was spreading rapidly throughout the country. During this period, passenger transportation was almost null due to the government's shelter-in-place order issued on March 24, allowing us to test the relationship between the trucking network topology and the number of COVID-19 cases reported at the municipality level. Table 1 shows the top five municipalities in Colombia according to the annual average number of trucks traveling inbound and outbound, relative to the total number of trips in the network. Cali (0.58), Barranquilla (0.54), Santa Marta (0.51) and Bogotá (0.51) were the municipalities reporting the highest infection rates per thousand inhabitants. In turn, they are among the municipalities with the highest levels of trucking activity. Notably, Barranquilla and Santa Marta are port-cities, and Cali is highly connected to the port-city of Buenaventura. Bogotá and Medellín are the most important centers of economic activity in Colombia.

As control variables for our model, we gathered data from the National Administrative Department of Statistics (DANE, for its acronym in Spanish) on (i) population (for 2019, the latest available information) and (ii) municipality relevance. DANE uses municipality relevance to classify Colombian municipalities into seven categories based on four criteria (i. e., economic relevance, financial capacity, geographical location, and population). The first category −called 'Special Category'− encompasses the most important municipalities in the country. The criteria of economic relevance −measured as a municipality's

Table 1
Main nodes in the trucking network and their COVID-19 infection rate as of May 6, 2020.

Node	Inbound (%)	Outbound (%)	COVID-19 cases per thousand inhabitants
Santa Marta	8.01	6.58	0.51
Cali	6.99	2.60	0.58
Bogotá	5.71	6.45	0.51
Medellín	5.15	5.86	0.18
Barranquilla	4.97	4.86	0.54

Notes: Node's relative importance to the national network. Own elaboration with data extracted from ONL.

contribution to the added value of a given Colombian region (i.e., Caribbean, Antioquia, etc.)– is used as an independent variable to control for the variability in economic activity among municipalities belonging to the same category of relevance. Finally, a dummy variable was created that takes the value of one if the node is a seaport municipality or zero otherwise. Table 2 presents the descriptive statistics at the municipality level, according to the data collected:

Gephi (Bastian et al., 2009) was used to visualize the trucking network in Colombia, modelling nodes' and links' characteristics to uncover the network topology. Using network analysis allows us to overcome the limitations of simple spatial association, which has been proven to be a poor predictor of disease spatial spreads unless there is connectivity between potential spreaders (Iacus et al., 2020). Then, following Wang et al. (2011) and Calatayud et al. (2017), network metrics, shown in Table 3, were applied.

These metrics were calculated and used to test the association between the trucking network topology and the spatial distribution of COVID-19 cases. To model this association, we need to consider three features of the dependent variable: first, the accumulated number of COVID-19 cases is a count variable and must be modeled accordingly; second, by May 6, 2020, only 30% of Colombian municipalities reported COVID-19 cases, so the value for the rest of municipalities equals zero; third, as shown in Table 2, the variable presents overdispersion with a coefficient of variation equal to seven, meaning that some municipalities were already significantly more affected than others during the time frame considered in this study. Taking into account this level of variation, we follow Cameron and Trivedi (2005) in applying a zero-inflated negative binomial specification to statistically test the potential spread of the COVID-19 virus through the trucking network by maximizing a likelihood function that is a combination of the logistic and the negative binomial probability distributions. The logistic distribution enables testing for the extensive margin of the virus, i. e., if the municipality belongs to the group not reached by the virus by May 6, as a function of the seaport condition of the municipality or belonging to the Special Category in the DANE classification. In turn, the negative binomial distribution enables testing for the intensive margin or the association between the trucking network metrics and the number of COVID-19 accumulated cases at the municipality level.

The likelihood function takes the following inputs (Array 1):

- y_i
- $\varepsilon_i^{\gamma} = \gamma_1 Seaport_i + \gamma_2 SpecialCategory_i + \varnothing_i$
- $\varepsilon_i^{\beta} = \beta_1 DM_i + \beta_2 \ln(C_{Bi}) + \beta_3 C_{ci} + \beta_4 Population_i + \beta_5 MR_i + \beta_6 ER_i + \sum_{h=1}^{H-1} \sigma_h NC_{hi} + \theta_i$

$$\mu_i = \exp\left(\varepsilon_i^{\beta}\right) \quad (1)$$

- $p_i = 1/(1 + \alpha\mu_i)$
- $m = 1/\alpha$

Where y_i is the count of COVID-19 confirmed cases as of May 6, 2020, in municipality i; *Seaport* takes the value of one if municipality i has a seaport condition in the network or zero otherwise, and *SpecialCategory* does the same whenever the municipality i is part of the most relevant category of municipalities according to DANE. DM_i stands for degree metrics and take the form of k_i^T, $k_i^{in}(t)$, $Wk_i^{in}(t)$, and $Wk_i^{out}(t)$ in each model; we estimate various models with different degree metrics to avoid problems of collinearity. C_{Bi} and C_{ci} represent betweenness and closeness centrality, respectively. MR_i is the municipality relevance; and ER_i is the economic relevance. $\varnothing_i$ and θ_i represent the idiosyncratic errors of each component. Also, from the network topology analysis, we retrieve the number of communities highly connected in the network by optimizing the level of modularity, i. e, the fraction of the edges that fall within a given partition of C communities minus the expected fraction if edges were randomly distributed. According to Leicht and Newman (2008), the modularity of a directed network (Q_d), like the trucking network in this context, can be represented formally as Equation (2):

$$Q_d = \frac{1}{\vartheta} \sum_{ij} \left[A_{ij} - \frac{k_i^{in}(t) k_i^{out}(t)}{\vartheta} \right] \delta(c_i, c_j) \quad (2)$$

Where ϑ stands for the number of edges in the network, A_{ij} represents the existence of an arc between nodes i and j, c is the community to which node i or j belong, and the δ-function $\delta(u, v)$ takes the value of one if $u = v$, and zero otherwise. We obtain the optimal number of communities using the algorithm developed by Blondel et al. (2008). Next, to capture common baseline variation among nodes that belong to the same community, the model introduces NC as a set of H variables which take the value of one in the case the municipality i belongs to the network community h and zero otherwise. Finally, the parameter α is the negative binomial overdispersion parameter; and parameters μ_i, p_i, and m are the standard parameters of the negative binomial probability distribution.

Therefore, we obtain the parameters γ, β, and σ, that optimize the log-likelihood function presented in Equation (3):

$$lnL = \sum_{i \in S} \ln\left\{F(\varepsilon_i^{\gamma}) + (1 - F(\varepsilon_i^{\gamma}))p_i^m\right\} +$$

$$\sum_{i \notin S} \Big\{ \ln(1 - F(\varepsilon_i^{\gamma})) + \ln\Gamma(m + y_i) - \ln\Gamma(y_i + 1) \quad (3)$$

$$- \ln\Gamma(m) + m \ln p_i + y_i \ln(1 - p_i)\Big\}$$

Where S is the set of municipalities with no COVID-19 cases by May 6, 2020 (i.e., $y_i = 0$); and F and Γ are the standard logistic and gamma probability distribution functions, respectively. Finally, statistical inference is obtained by clustering standard errors at the community level.

Table 2
Descriptive statistics at the municipality level.

Variable	Municipalities	Mean	S. D.	Min	Max
COVID-19 cases	156	44.6	312.9	0.0	3688.0
Population (thousands)	156	125.5	629.8	1.8	7181.5
Inbound trips	156	221.7	477.6	15.4	2987.1
Outbound trips	156	221.7	430.0	15.0	2360.7
Municipality relevance	156	5.3	1.7	1.0	7.0
Economic relevance	156	4.9	14.1	0.1	100.0
Seaport	156	0.03	0.2	0.0	1.0

5. Results

Fig. 2 shows the trucking network in Colombia. The network has 156 nodes corresponding to the municipalities of origin or destination and 3780 links corresponding to O-D trucking trips reported in the ONL representative sample. According to their degree centrality, the network has a hub-and-spoke configuration, with eight municipalities emerging as main hubs: Santa Marta, Cali, Bogotá, Medellín, Barranquilla, Maicao, Cartagena de Indias, and Cúcuta. Except for Maicao and Santa Marta, hubs concur with the municipalities belonging to the Special Category–the most relevant municipalities in Colombia–in the DANE classification. Located at the border with Venezuela, the connectivity of Maicao is explained by its role as a critical hub for international trade and freight transportation.

Municipalities more strongly connected by a higher number of O-D trips form a community. The trucking network in Colombia is organized around five communities (Fig. 2), concentrated around a central node. These central nodes are:

Table 3
Network metrics.

Metric	Definition	Formula
In-degree	The number of links a node i receives from other nodes j in moment t. In our research, it refers to the number of trucking routes finishing at a given municipality.	$k_i^{in}(t) = \sum_{j=1}^{N(t)} a_{ij}(t)$
Out-degree	The number of links a node i sends to other nodes j in moment t. In our research, it is the number of trucking routes originating at a given municipality.	$k_i^{out}(t) = \sum_{j=1}^{N(t)} a_{ji}(t)$
Degree	The sum of in and out degrees.	$k_i^T(t) = k_i^{in}(t) + k_i^{out}(t)$
Weighted in-degree	In-degree pondered by the weight of each link. In our research, it is pondered by the number of trucking trips received by a municipality.	$Wk_i^{in}(t) = \sum_{j=1}^{N(t)} a_{ij}(t)^* w_{ij}(t)$
Weighted out-degree	Out-degree pondered by the weight of each link. In our research, pondered by the number of trucking trips originating at a municipality.	$Wk_i^{out}(t) = \sum_{j=1}^{N(t)} a_{ji}(t)^* w_{ji}(t)$
Betweenness centrality	The extent to which a particular municipality i is located on the shortest trucking route connecting other municipalities j and k in the network.	$C_{Bi} = \sum_{k \neq i \neq j \in N} \sigma_{kj}(i) / \sigma_{kj}$
Closeness centrality	The extent to which a municipality i is close to all other municipalities j along the shortest routes, reflecting its level of accessibility in the trucking network.	$C_{ci} = \frac{n-1}{\sum_{v_j \in V, i \neq j} d_{ij}}$

Source: Own elaboration based on Wang et al. (2011) and Calatayud et al. (2017).

- Bogotá (in light green in Fig. 2), agglomerating 25.6% of total network's nodes, which are located in the central area of the country and supply the Bogotá area with different types of goods;
- Santa Marta (in purple), closely linked to 23.7% of nodes in the network, which are mostly located on the Caribbean coast, connected to them by trucking trips carrying import and export goods to/from the main seaports in the country;
- Medellín (in blue), agglomerating 18.6% of nodes, which are on the western part of the country and supply the Medellín area with different types of goods;
- Cali (in orange), tightly connected to 23.1% of the nodes through trucking trips for domestic and international markets (through the port of Buenaventura, the largest in the country, and the border crossing with Ecuador at Ipiales);
- Cúcuta (in dark green), agglomerating 9% of the network nodes located on the border with Venezuela, connected through trucking trips carrying import and export goods to/from the border.

On average, each node is connected to seven other nodes in the network (Table 4). However, due to the network's hub-and-spoke configuration, the maximum number of connections is 56, equivalent to a third of the network's nodes. The nodes in the Caribbean community −in color purple in Fig. 2− concentrate almost a third of the total number of trips in the trucking network. This concentration level is explained by the area's relevance for international trade, with seaports in Barranquilla, Cartagena, and Santa Marta and a land border crossing in Maicao. These gateways are connected to domestic exporting and importing areas by road transportation.

Fig. 3 shows the trucking network in Colombia, combined with data on accumulated COVID-19 cases at the municipality level by May 6, 2020. The intensity of the blue color reflects the level of node infection. The different node sizes denote the number of trips they generate, with more significant nodes being the origin of more trucking activity. Bogotá is the most affected node in the network regarding the count of COVID-19 cases, which is 3.5 times greater than Cali, the second node with the highest contagion level. Both nodes generate 9.1% of total trips in the network, with primary destinations located in the southwestern part of the country, mainly the border crossing with Ecuador −Ipiales− and the port of Buenaventura. Despite the lower nominal infection levels of Barranquilla, Cartagena de Indias, and Santa Marta, it is worth noting that the three belong to the same community −the Caribbean community− thus being closely connected by a high number of daily trips.

Table 5 reports the results from the model. The logistic regression results indicate that nodes that are port-cities or belong to the Special Category in the DANE classification have a higher probability of being part of the infected nodes during the initial phase of a viral disease outbreak. Indeed, by May 6, 2020, all cities in the Special Category had

Table 4
Colombian trucking network metrics.

Variable	Mean	S. D.	Max
Degree (k^t)	7.1	10.2	56.0
In-degree (k^{in})	3.5	5.1	27.0
Weighted degree	443.5	882.1	5347.9
Weighted in-degree (Wk^{in})	1552.1	3343.5	20,910
Weighted out-degree (Wk^{out})	1552.1	3010.3	16,525
Ln(Betweenness) (ln C_b)	2.65	3.18	9.7
Closeness (C_c)	0.28	0.22	1.0

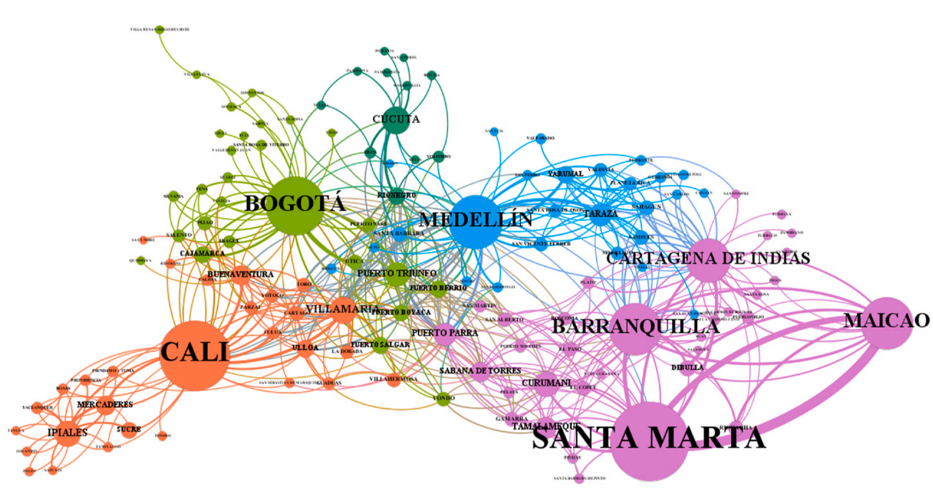

Fig. 2. Trucking network in Colombia.
Notes: The nodes' size reflects the number of inbound trucks, and the size of the links represents the number of trips between pairs of nodes (i.e., weight). Colors identify the community's nodes. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
Source: Own elaboration in Gephi with data from ONL.

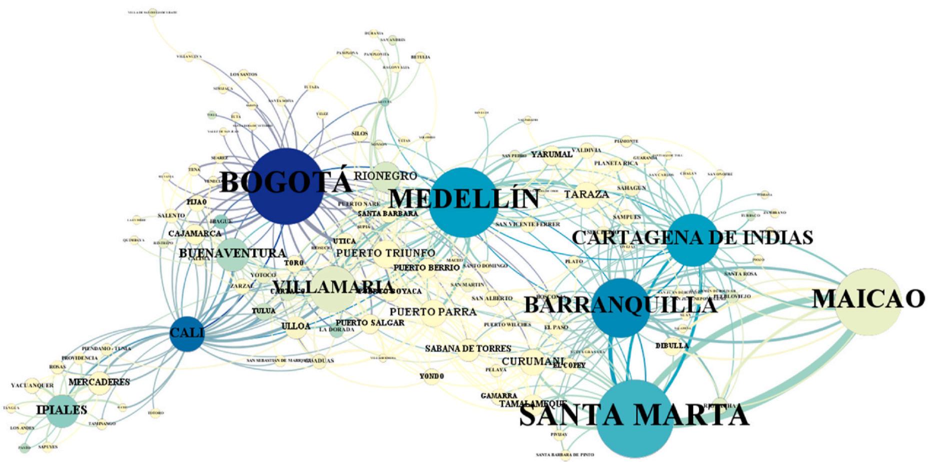

Fig. 3. Trucking network in Colombia and accumulated COVID-19 cases.
Notes: The blue color intensity relates to the number of confirmed cases until May 6, 2020. Deep blue means higher number of cases, with Bogotá reporting the highest number. Node sizes are according to the number of truck trips they generate. Link size represents the number of truck trips between pairs of nodes. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
Source: Own elaboration in Gephi with data extracted from ONL and official COVID-19 records.

Table 5
Model results.

	Negative binomial				
	(1)	(2)	(3)	(4)	(5)
	IRR				
Degree (k^t)	1.04				
	(1.06)				
In-degree (k^{in})		1.12***			
		(3.78)			
Weighted degree (Wk^T)			1.00005***		
			(2.71)		
Weighted in-degree (Wk^{in})				1.00008***	1.00007***
				(4.97)	(2.91)
Weighted out-degree (Wk^{out})					1.000024
					(0.48)
Ln(Betweenness) ($\ln\ C_b$)	0.75**	0.76**	0.79**	0.81**	0.80**
	(-2.31)	(-3.43)	(-2.51)	(-2.19)	(-2.47)
Closeness (C_c)	9.37*	11.60**	8.26*	9.57*	8.89*
	(1.91)	(2.20)	(1.71)	(1.94)	(1.72)
Network community 1 (NC_1, *hub Bogotá*)	258.48*	89.33**	262.09**	191.91**	219.40**
	(1.87)	(2.20)	(2.18)	(2.50)	(2.16)
Network community 2 (NC_2, *hub Cali*)	286.76*	56.75*	237.71**	148.45**	179.72**
	(1.91)	(1.93)	(2.14)	(2.30)	(1.98)
Network community 3 (NC_3, *hub Santa Marta*)	176.83*	38.03*	126.17**	84.98**	98.94*
	(1.67)	(1.70)	(1.95)	(2.13)	(1.84)
Network community 4 (NC_4, *hub Medellín*)	90.76	19.07	68.77*	45.40*	53.46
	(1.52)	(1.39)	(1.71)	(1.82)	(1.58)
Network community 5 (NC_5, *hub Cúcuta*)	57.10	16.02*	85.21*	54.42*	66.78
	(1.24)	(1.26)	(1.67)	(1.85)	(1.57)
	Logit				
Seaport	−14.23***	−14.52***	−15.46***	−15.27***	−14.78***
	(-15.47)	(-19.94)	(-20.56)	(-20.71)	(-20.32)
Special Category	−14.45***	−14.31***	−15.25***	−15.03***	−14.98***
	(-12.15)	(-14.76)	(-15.23)	(-15.83)	(-15.77)
Constant	0.16	0.43	0.37	0.43	0.42
	(0.16)	(0.57)	(0.64)	(0.60)	(0.58)
α	0.89	0.63	0.39	0.63	0.64
log pseudolikelihood	−230.01	−229.29	−229.49	−229.48	−229.45

Notes: All specifications control for population, MR, and ER. IRR stands for incidence-rate ratios. Z-statistic reported in parenthesis. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *.

reported COVID-19 cases. If a node does not belong to either of these categories, the predicted probability of being reached by the virus at the beginning of the pandemic is 0.6. Instead, the predicted probability is close to 1 when municipalities are both a port-city and belong to the Special Category. Indeed, Barranquilla, Cartagena de Indias, and Santa Marta reported COVID-19 cases by May 6, 2020.

Next, we used the negative binomial estimation to understand the intensive margin or the association between the trucking network metrics and the number of COVID-19 accumulated cases by the node during the first three months of the pandemic. Each column in Table 5 reports results for model testing for a different measure of degree centrality. Total degree centrality (column 1) reports a positive association, but it is not statistically significant at any level. Conversely, in-degree centrality (column 2) reports a positive and significant association at the 1% level, meaning that one more inbound trucking route was associated with a 12% increase of COVID-19 cases.

The models reported in columns (3) and (4) consider the nodes' total weighted degree and weighted in-degree, both reporting a statistically significant effect. In addition, the sequence of models and the z critic value shows that the overall effect is generated mainly by the weighted in-degree effect (column 5). These results suggest that an increase of a half standard deviation in the number of inbound trucks (i.e., 1671.5 more trucks) was associated with an average increase of 13% confirmed COVID-19 cases between March and May 2020.

Closeness centrality is positively and strongly associated with contagion at the 10% confidence level. This result suggests that a one-percentage-point increase in a node's closeness centrality was associated with an increase of 9.7 COVID-19 cases at the beginning of the pandemic. In other words, the more strategically positioned a municipality is in the trucking network, the higher the risk of contagion.

Finally, there is a positive community effect on the number of cases reported by nodes in the same communities. Municipalities that are closely connected to nodes with the highest degree of centrality in the network (i.e., nodes in the community of Santa Marta and Bogotá), and municipalities linked to main seaports (i.e., nodes highly connected to Barranquilla, Cartagena de Indias, Santa Marta, or Cali) were expected to have a higher number of COVID-19 cases at the beginning of the pandemic.

Table 6 uses the results from models reported in columns (2) and (4) as inputs to present the predicted number of confirmed COVID-19 cases associated with trucking activity for those nodes that had already been reached by the pandemic (i.e., nodes with at least one confirmed case) by May 6, 2020. Predictions are presented for different in-degree values and weighted in-degree centrality considering an average node in each network community. The first row in Table 6 shows the predicted number of COVID-19 cases associated with trucking activities for the average node at the beginning of an infectious disease pandemic like COVID-19. The node's in-degree and weighted in-degree centralities in the light green community (which hub is Bogotá) are 4.8 and 2,560, respectively. For this node, the predicted number of cases related directly to trucking activities amounts to 13. An additional inbound route or 1500 more inbound trucks would increase the predicted number of cases to 15. An increase of one standard deviation of inbound routes and the number of inbound trucks−which in this community would equal 9.4 a 5497.1, respectively−, would increase the prediction to 38 and 21 confirmed cases holding all other things being equal. These cases are related directly to trucking activities. However, given that infectious diseases like COVID-19 expand rapidly through social networks, indirect cases are expected to be significantly higher.

Table 6
Predicted number of COVID-19 cases according to nodes attributes.

Prediction at	Community				
In-degree (model 2); W. In-degree (model 4)	Light Green (hub Bogota)	Orange (hub Cali)	Purple (hub Santa Marta)	Blue (hub Medellin)	Dark green (hub Cucuta)
Mean (baseline)	13.3*; 13.4**	7.3; 7.6	13.4; 7.6	2.1; 2.2	5.5; 5.6
+1; +1500	14.8; 15.2	8.2; 8.6	14.9; 8.6	2.4; 2.5	6.1; 6.4
+1 S.D.	37.6; 21.2	15.7; 11.3	35.6; 11.3	5.4; 3.3	11.4; 7.5
+2 S.D.	106.4; 33.6	33.9; 16.9	95.57; 16.7	13.9; 4.9	23.7; 10.1
+3 S.D.	301.3; 53.3	72.9; 25.2	259.5; 25.2	35.7; 7.2	49.5; 13.6

Notes: Prediction for the subsample of nodes with positive COVID-19 cases (i.e., excludes nodes with no cases) are all statistically significant at the 1% level. *Predicted cases according to in-degree centrality; **Predicted cases according to weighted in-degree centrality.

6. Discussion

By understanding the topology of the trucking network, useful information can be gathered and used to prevent the network from spreading infectious diseases. Literature in epidemiology uncovered the relationship between trucking activities and both sexually transmitted and blood-borne diseases (Apostolopoulos and Sönmez, 2007). This paper shows that road freight transportation can also help disseminate viral infections throughout the trucking network. We first identify the main attributes that make a node in the network more susceptible to be infected early during a virus outbreak; this allows us to overcome the limitations of spatial association, which has been proven to be a poor predictor of contagion unless there is connectivity between potential spreaders (Iacus et al., 2020). In the case of Colombia, being a port-city, belonging to the Special Category of the DANE classification, and having a higher in-degree, weighted in-degree, or closeness centrality are all attributes that indicate a node's higher exposure to contagion. Next, we show how an infectious disease can be spread through the trucking network. Like in the case of air travel (Yang et al., 2015), the trucking network's hub-and-spoke configuration increases a node's probability of infection once the hub in its community has become infected by the virus. For example, when Bogotá and Cali reported their first COVID-19 cases, their neighbors' likelihood of being infected increased to 39% and 41% in the first months, respectively. Moreover, our findings suggest that a combination of being a port-city, belonging to the Special Category, and having a high (weighted) in-degree centrality significantly enhances a node's potential to disseminate the virus across the network. This is the case of the central nodes in the Caribbean community, namely Barranquilla, Cartagena de Indias, and Santa Marta, which, among all other nodes on the trucking network, have the highest capacity to spread the virus not only within their community but throughout the entire network.

The containment measures implemented in Colombia at the beginning of the pandemic included a nationwide lockdown −Presidential Decree 457 of March 19, 2020− while allowing the continuity of all trucking activities to ensure the supply of essential goods. Moreover, Article 3.16 of the Presidential Decree allowed resuming port activities related to the freight network. The COVID-19 safety protocols for the trucking industry were issued on April 24, 2020. While these measures were critical to reduce the risk of COVID-19 contagion, other countries, such as China and Singapore, established measures more specifically related to the trucking network particularities−i.e., green corridors− to mitigate virus propagation through trucking activities. Rio de Janeiro was one of the few cases in Latin America that adopted measures in this sense: in March 2020, trucking activity was restricted for 15 days between the metropolitan region and other municipalities in the state of Rio de Janeiro.

Understanding and measuring the risks posed by the trucking network provides insightful information to design virus containment measures. At the same time, it is unrealistic to monitor the entire network completely−each day, there are approximately 35,000 trips in the Colombian network (MinTransporte, 2019). Identifying and surveilling corridors, areas, and nodes at high risk of contagion can assist in effectively mitigating the risk of virus dissemination while ensuring the continuity of the supply chain. To illustrate this, in Fig. 4, we present the geographical configuration of the trucking network in Colombia. Given the high virus dissemination potential of the Caribbean community, our findings suggest focusing containment measures on the corridors connecting: (i) municipalities in this community (Roads 90 and 80); (ii) Caribbean ports with Bogotá (Highway 45, and sections of highways 6209 and 5501); and (iii) Caribbean ports with Medellín (Roads 2511 through 2516). In addition, the high number of COVID-19 cases in Bogotá and its central role in the network and community suggest that this should be one priority area to implement containment measures. Another priority area should be the connection between Cali and the international gateways in Buenaventura and Ipiales (Highways 4001,

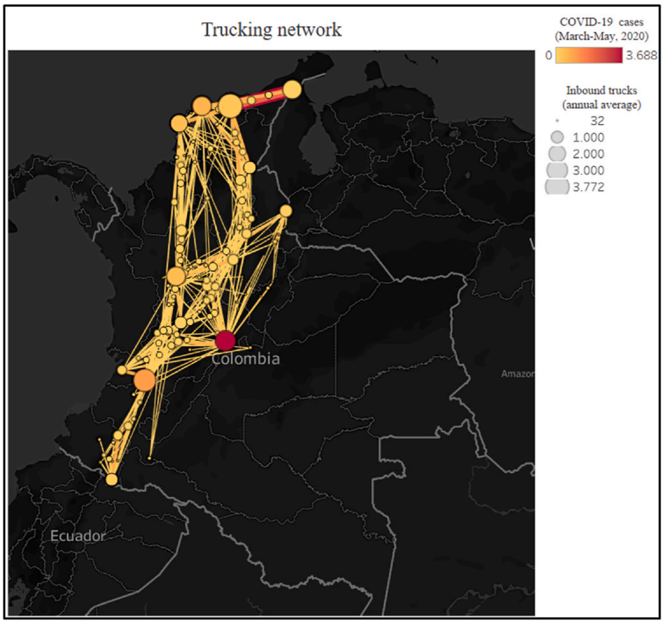

Fig. 4. Colombia's trucking network (2010–2016, sample annual average).
Notes: Nodes' size according to their total degree centrality. Links' size according to their total weight. The color intensity of the nodes corresponds to the number of COVID-19 confirmed cases; red meaning a higher number of cases. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
Source: Own elaboration with data from ONL and Open Data Colombia.

2501, and 2504).

The containment measures implemented worldwide during the first waves of COVID-19 in 2020 show that governments can rely on different courses of action to reduce virus dissemination. The challenge, however, is to achieve risk mitigation while avoiding disrupting supply chains. The approach implemented in this paper provides policymakers with a practical tool to diagnose and classify trucking connections according to their level of risk. Consequently, policy measures can be customized according to such levels. For low-risk connections –i.e., those between nodes with low network centrality– measures may limit to requiring truck drivers to wear masks and reporting their temperature at trip origin and destination (facility-level). For high-risk connections –i.e., those in the Caribbean community– checkpoints may be needed at the trip origin, destination, and intermediate stops (node-level), where truck drivers may present health declaration forms, negative polymerase chain reaction (PCR) test results, cargo documents, and other information to prove that neither they nor the cargo has been exposed to the virus. According to risk levels, customizing containment measures can also help lift restrictions progressively once cases subside while maintaining risk surveillance.

As suggested by Mao and Bian (2010), it should be noted that there are limitations in applying this type of analysis prior to an epidemic emergency since the accurate calibration of transmission models requires data that can only be collected post-event. Virus mutations may also affect the reliability of results. Nevertheless, available literature has shown that these analyses can still provide useful guidance to design transmission mitigation actions at the beginning of an epidemic outbreak, including restricting travel from affected nodes and focusing immunization strategies on the nodes with the highest betweenness centrality (Yang et al., 2015; Yang and Wang 2016). In addition, the validity of findings relies on data quality and consistency across municipalities. In the case of Colombia, this risk is mitigated given that data collection and management is centralized at the national level and the same data management protocols are applied to all municipalities.

7. Conclusions

Combining network, statistics, and geographic analysis of road freight transportation can help policymakers design risk-based strategies to mitigate the expansion of COVID-19-like diseases at the national level while avoiding supply chain disruptions. This paper showed that the Colombian trucking network has a hub-and-spoke configuration, with five highly connected communities. Bogotá, Cali, Cúcuta, Medellín, and Santa Marta are the network hubs that enable connectivity between communities. In line with previous research on virus dissemination through transport networks, our results show that these hubs have a high potential to spread contagion towards other hubs, as well as nodes in their community. Moreover, the statistical model's findings suggest that the number of COVID-19 cases in a city is linked to its level and type of network centrality. Indeed, each additional inbound link is associated with a 12% increase in the number of COVID-19 reported cases. Likewise, being a port city and a primary economic hub in the trucking network is associated with a higher probability of being reached earlier by a pandemic.

While it is unrealistic to thoroughly monitor an extensive network with approximately 35,000 trips per day, identifying and surveilling corridors, areas, and nodes at high risk of contagion can effectively mitigate the risk of virus dissemination. We thus suggest adopting a risk-based approach combining network topology and epidemiological information. Based on the information gathered from Colombia at the beginning of the pandemic, which can also apply to future virus outbreaks similar to COVID-19, the main containment measures should be applied on the corridors connecting: (i) municipalities in the Caribbean community (Roads 90 and 80); (ii) Caribbean ports with Bogotá (Highway 45, and sections of highways 6209 and 5501); and (iii) Caribbean ports with Medellín (Roads 2511 through 2516). Moreover, Bogotá's central role for the trucking network and its community suggests that this should be one priority area to implement containment measures. Another priority area should be the connection between Cali and the international gateways in Buenaventura and Ipiales (Highways 4001, 2501, and 2504). Further work could focus on applying the methodology and approach proposed to other countries, both in Latin America and other regions, as a means to provide policymakers with a broader understanding of virus dissemination through transport networks.

Annex.

After the March–May 2020, outbreak of COVID-19 in Colombia, the country has gone through additional waves of increased cases; the first one starting during the last months of 2020 and reaching its maximum number of positive cases in January 2021, and the second one starting during March 2021, and reaching its peak at the end of June 2021. We test the predictive fit of the model in light of these contagion peaks.

To conduct such an analysis, it is necessary to measure variation in trucking activity within the Colombian network. However, there is no data source reporting trucking activity on a daily or weekly basis. We approach this issue by leveraging internet activity as a proxy of public interest in trucking activity, considering that the correlation between internet trends and actual activity has proven high and valid for empirical studies (Mavragani et al., 2018). We collected weekly data on the Google number of searches for "trucks," "roads," "freight," "freight transportation," and "supplies" (in Spanish) in Colombia during the timeframe of January 1, 2020, to August 10, 2021. Next, we conducted a principal component analysis

(PCA) to capture the common variability of public interest on these topics across weeks. All variables correlate positively with the first found component, which has an eigenvalue of 1.6 and explains 31% of the total variability. We take the prediction of this principal component as a proxy of public interest in trucking activity to conduct marginal predictions on the level of contagion in different moments for a group of nodes in the network.

The analysis considers critical dates on contagion during the peaks mentioned above, namely August 3, 2020; January 11, 2021; and April 13, 2021. We take the variation in the predicted principal component one month before each of these dates, with respect to a typical week before the pandemic (the one of February 2, 2020), as a reasonable timeframe to see any possible effect in the confirmed number of COVID19 cases. Table 7 compares the marginal prediction vs. the observed number of COVID19 cases for the main hubs of the network. Since this is not an epidemiological approach, it is not expected to precisely forecast the number of confirmed cases, but it consistently replicates the variation in the number of cases across peak dates for every hub of the trucking network.

Table 7
Marginal prediction vs. observed confirmed number of COVID-19 cases during contagion peaks.

Date of report (Reference date, % change in trucking principal component)	Community hub									
	Bogota		Cali		Santa Marta		Medellín		Cúcuta	
	Predicted	Observed	Predicted	Observed	Predicted	Observed	Predicted	Observed	Predicted	Observed
August 3, 2020	3039	3632	2360	667	264	157	475	873	24	290
(July 5, 2020, +23%)	[1041 - 5036]		[1009 - 3711]		[184–346]		[368–583]		[11–36]	
Jan 11, 2021	2592	3464	1880	583	207	30	405	565	22	26
(Dec 13, 2020, +9%)	[1005 - 4181]		[788 - 2974]		[153–262]		[313–497]		[10–34]	
April 13, 2021	3249	3909	2597	708	292	464	509	1590	25	70
(Mar 14, 2021, +29%)	[1041 - 5445]		[1110 - 4084]		[195–390]		[391–627]		[12–37]	

Notes: February 2, 2020, as the reference of trucking activity. The date considered for changes in trucking activity relative to February 2, 2020, is reported inside parenthesis along with the percentage change. 95% confidence intervals in brackets. All predictions are statistically significant at the 1% level.

References

Apostolopoulos, Y., Lemke, M., Sönmez, S., 2014. Risks endemic to long-haul trucking in North America: strategies to protect and promote driver well-being. New Solut. 24 (1), 57–81. https://doi.org/10.2190/NS.24.1.c.

Apostolopoulos, Y., Sönmez, S., 2007. Population mobility and infectious disease. In: Population Mobility and Infectious Disease. https://doi.org/10.1007/978-0-387-49711-2.

Apostolopoulos, Y., Sönmez, S., Hege, A., Lemke, M., 2016. Work strain, social isolation and mental health of long-haul truckers. Occup. Ther. Ment. Health 32 (1), 50–69. https://doi.org/10.1080/0164212X.2015.1093995.

Apostolopoulos, Y., Sönmez, S., Lemke, M.K., Rothenberg, R.B., 2015. Mapping U.S. long-haul truck drivers' multiplex networks and risk topography in inner-city neighborhoods. Health and Place. https://doi.org/10.1016/j.healthplace.2015.03.008.

Badr, H.S., Du, H., Marshall, M., Dong, E., Squire, M.M., Gardner, L.M., 2020. Association between mobility patterns and COVID-19 transmission in the USA: a mathematical modelling study. Lancet Infect. Dis. https://doi.org/10.1016/S1473-3099(20)30553-3.

Bajunirwe, F., Izudi, J., Asiimwe, S., 2020. Long-distance truck drivers and the increasing risk of COVID-19 spread in Uganda. Int. J. Infect. Dis. 98, 191–193. https://doi.org/10.1016/j.ijid.2020.06.085.

Balcan, D., Vespignani, A., 2011. Phase transitions in contagion processes mediated by recurrent mobility patterns. Nat. Phys. https://doi.org/10.1038/nphys1944.

Barbero, J., Guerrero, P., 2017. El transporte automotor de carga en América Latina. https://publications.iadb.org/publications/spanish/document/El-transporte-automotor-decarga-en-América-Latina-Soporte-logístico-de-la-producción-y-el-comercio.pdf.

Bastian, M., Heymann, S., Jacomy, M., 2009. Gephi: an open source software for exploring and manipulating networks. In: International AAAI Conference on Weblogs and Social Media.

Bian, L., Liebner, D., 2007. A network model for dispersion of communicable diseases. Trans. GIS. https://doi.org/10.1111/j.1467-9671.2007.01039.x.

Blondel, V.D., Guillaume, J.L., Lambiotte, R., Lefebvre, E., 2008. Fast unfolding of communities in large networks. J. Stat. Mech. Theor. Exp. 2008(10).

Calatayud, A., Mangan, J., Palacin, R., 2017. Connectivity to international markets: a multi-layered network approach. J. Transport Geogr. https://doi.org/10.1016/j.jtrangeo.2017.04.006.

Cameron, A.C., Trivedi, P.K., 2005. In: Microeconometrics: Methods and Applications. Cambridge University Press, New York.

Carlitz, R.D., Makhura, M.N., 2021. Life under lockdown: illustrating tradeoffs in South Africa's response to COVID-19. World Dev. 137 https://doi.org/10.1016/j.worlddev.2020.105168.

El Tiempo, 2001. El 85 del transporte de carga es informal. https://www.eltiempo.com/archivo/documento/MAM-683369.

Gachohi, J., Aduda, J., Thuo, R., Mung'atu, J., Wamunyokoli, F., Ngigi, T., Athiany, H., Kikuvi, G., Mambo, S., Gichaiya, W., Matheri, J., Mburugu, P., Simba, J., Otiwa, C., Muriuki, C., Mwaura, J., Yariwo, M., Kariuki, B., Machua, J., et al., 2020. Public health challenges posed by delays in obtaining COVID-19 clearance for long-distance truckers across East Africa. Global Epidemiol. 2, 100039. https://doi.org/10.1016/j.gloepi.2020.100039.

Harris, J.E., 2020. The subways seeded the massive coronavirus epidemic in New York city. SSRN Electron. J. https://doi.org/10.2139/ssrn.3574455.

Iacus, S.M., Santamaria, C., Sermi, F., Spyratos, S., Tarchi, D., Vespe, M., 2020. Human mobility and COVID-19 initial dynamics. Nonlinear Dynam. https://doi.org/10.1007/s11071-020-05854-6.

INS, 2021. COVID-19 en Colombia. Casos. https://www.ins.gov.co/Noticias/Paginas/coronavirus-casos.aspx.

Khan, K., Arino, J., Hu, W., Raposo, P., Sears, J., Calderon, F., Gardam, M., et al., 2009. Spread of a novel influenza A (H1N1) virus via global airline transportation. New England J. Med. 361 (2), 212–214.

Kitsak, M., Gallos, L.K., Havlin, S., Liljeros, F., Muchnik, L., Stanley, H.E., Makse, H.A., 2010. Identification of influential spreaders in complex networks. Nat. Phys. https://doi.org/10.1038/nphys1746.

Kraemer, M.U.G., Yang, C.H., Gutierrez, B., Wu, C.H., Klein, B., Pigott, D.M., du Plessis, L., Faria, N.R., Li, R., Hanage, W.P., Brownstein, J.S., Layan, M., Vespignani, A., Tian, H., Dye, C., Pybus, O.G., Scarpino, S.V., 2020. The effect of human mobility and control measures on the COVID-19 epidemic in China. Science. https://doi.org/10.1126/science.abb4218.

Kretzschmar, M., Morris, M., 1996. Measures of concurrency in networks and the spread of infectious disease. Math. Biosci. https://doi.org/10.1016/0025-5564(95)00093-3.

Lawal, O., Nwegbu, C., 2020. Movement and risk perception: evidence from spatial analysis of mobile phone-based mobility during the COVID-19 lockdown, Nigeria. GeoJournal. https://doi.org/10.1007/s10708-020-10331-z.

Leicht, E.A., Newman, M.E.J., 2008. Community structure in directed networks. Phys. Rev. Lett. 100 (11), 118703. https://doi.org/10.1103/PhysRevLett.100.118703.

Li, J., Xiang, T., He, L., 2021. ScienceDirect Modeling epidemic spread in transportation networks : a review. J. Traffic Transport. Eng. 1–14. https://doi.org/10.1016/j.jtte.2020.10.003 (English Edition), January.

Liu, P., Yang, M., Zhao, X., Guo, Y., Wang, L., Zhang, J., Lei, W., Han, W., Jiang, F., Liu, W.J., Gao, G.F., Wu, G., 2020. Cold-chain transportation in the frozen food industry may have caused a recurrence of COVID-19 cases in destination: successful isolation of SARS-CoV-2 virus from the imported frozen cod package surface. Biosaf. Health 2 (4), 199–201. https://doi.org/10.1016/j.bsheal.2020.11.003.

Logistics Cluster, 2014. Colombia Road Network. Logistics Capacity Assessment. https://dlca.logcluster.org/display/public/DLCA/2.3+Colombia+Road+Network.

Londoño-Kent, M.P., 2007. Road Freight Transport Industry in Low and Middle Income Countries.

Mao, L., Bian, L., 2010. A dynamic network with individual mobility for designing vaccination strategies. Trans. GIS. https://doi.org/10.1111/j.1467-9671.2010.01201.x.

Mavragani, A., Ochoa, G., Tsagarakis, K.P., 2018. Assessing the methods, tools, and statistical approaches in Google trends research: systematic review. J. Med. Internet Res. https://doi.org/10.2196/jmir.9366.

Meloni, S., Arenas, A., Moreno, Y., 2009. Traffic-driven epidemic spreading in finite-size scale-free networks. Proc. Natl. Acad. Sci. U.S.A. https://doi.org/10.1073/pnas.0907121106.

Minsalud, 2020. Medidas de protección para trabajadores y pasajeros del sector transporte. https://www.minsalud.gov.co/Paginas/Medidas-de-proteccion-para-trabajadores-y-pasajeros-del-sector-transporte.aspx.

Minsalud, 2021. Coronavirus (COVID-19). Prevención Enfermedades Transmisibles. https://www.minsalud.gov.co/salud/publica/PET/Paginas/Covid-19_copia.aspx.

MinTransporte, 2019. Transporte en Cifras. https://www.mintransporte.gov.co/documentos/15/estadisticas/.

MinTransporte, 2020. Noticias del sector transporte. https://www.mintransporte.gov.co/publicaciones/noticias/?tema=323.

Poletto, C., Tizzoni, M., Colizza, V., 2012. Heterogeneous length of stay of hosts' movements and spatial epidemic spread. Sci. Rep. https://doi.org/10.1038/srep00476.

Ranney, M.L., Griffeth, V., Jha, A.K., 2020. Critical supply shortages — the need for ventilators and personal protective equipment during the Covid-19 pandemic. N. Engl. J. Med. https://doi.org/10.1056/nejmp2006141.

Wang, J., Mo, H., Wang, F., Jin, F., 2011. Exploring the network structure and nodal centrality of China's air transport network: a complex network approach. J. Transport Geogr. https://doi.org/10.1016/j.jtrangeo.2010.08.012.

Xu, F., Connell McCluskey, C., Cressman, R., 2013. Spatial spread of an epidemic through public transportation systems with a hub. Math. Biosci. https://doi.org/10.1016/j.mbs.2013.08.014.

Yang, H.X., Tang, M., Lai, Y.C., 2015. Traffic-driven epidemic spreading in correlated networks. Phys. Rev. E - Stat. Nonlinear Soft Matter Phys. https://doi.org/10.1103/PhysRevE.91.062817.

Yang, H.X., Wang, B.H., 2016. Immunization of traffic-driven epidemic spreading. Phys. Rev. E - Stat. Nonlinear Soft Matter Phys. https://doi.org/10.1016/j.physa.2015.09.079.

Zhang, C., Qian, L.X., Hu, J.Q., 2020. COVID-19 pandemic with human mobility across countries. J. Oper. Res. Soc. China. https://doi.org/10.1007/s40305-020-00317-6.

Zhao, S., Zhuang, Z., Cao, P., Ran, J., Gao, D., Lou, Y., Yang, L., Cai, Y., Wang, W., He, D., Wang, M.H., 2020. Quantifying the association between domestic travel and the exportation of novel coronavirus (2019-nCoV) cases from Wuhan, China in 2020: a correlational analysis. J. Trav. Med. https://doi.org/10.1093/jtm/taaa022.